ASTRAPÉ CONSULTING
innovation in electric system planning

DESC 2023 Planning Reserve Margin Study

Final Report

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PREPARED FOR

Dominion Energy South Carolina

PREPARED BY

Astrapé Consulting

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ABBREVIATIONS USED IN REPORT

BAA	Balancing Authority Area
BESS	Battery Energy Storage System
CC	Combined Cycle Generator
CT	Combustion Turbine Generator
DESC	Dominion Energy South Carolina
DR	Demand Response
EE	Energy Efficiency
EFOR	Equivalent Forced Outage Rate
EIA	Energy Information Authority
EIDB	Eastern Interconnection Data Base
ELCC	Effective Load Carrying Capability
EUE	Expected Unserved Energy
GADS	Generating Availability Data System
GDP	Gross Domestic Product
IRP	Integrated Resource Plan
LFE	Economic Load Forecast Error
LOLE	Loss of Load Expectation
MO	Maintenance Outage
NERC	North American Electric Reliability Corporation
NOAA	National Oceanic and Atmospheric Administration
NREL	National Renewable Energy Laboratory
NSRDB	National Solar Radiation Database
ORDC	Operating Reserve Demand Curve
PO	Planned Maintenance Outage
PRM	Planning Reserve Margin
TTF	Time to Fail
TTR	Time to Repair
SAM	NREL System Advisory Model
SERVM	Astrapé’s Strategic Energy and Risk Evaluation Model
SEPA	Southeastern Power Administration

EXECUTIVE SUMMARY

This document provides details concerning a two-fold study performed by Astrapé Consulting for Dominion Energy South Carolina (DESC) to accomplish the following goals:

1. Determine the Planning Reserve Margin (PRM) associated with the DESC system.
2. Determine the Effective Load Carrying Capability (ELCC) for a range of solar and battery energy storage system (BESS) penetrations on the DESC system.

The following summarizes the results of this study.

PRM RESULTS

The PRM of a system represents the amount of additional capacity in excess of forecasted peak load that the system would need in order to maintain an acceptable level of system reliability. In this study, this was accomplished by determining the amount of capacity that would be necessary to maintain a Loss of Load Expectation (LOLE) of 0.1 days/year. This level of reliability corresponds to an expectation of one loss of load event every 10 years, which is consistent with industry practice.

The base case PRM for the DESC system was performed for 2026. The 2026 study year represents the near term condition of the DESC system in the time period in which the next resource decisions may need to be made. The result of the study is a PRM of 20.1% winter reserve margin.

As shown in the figure below containing the monthly breakdown of LOLE at the PRM level closest to 0.1 LOLE, the overwhelming majority of LOLE occurs in the winter, making winter the dominant season for establishing reliability criteria.

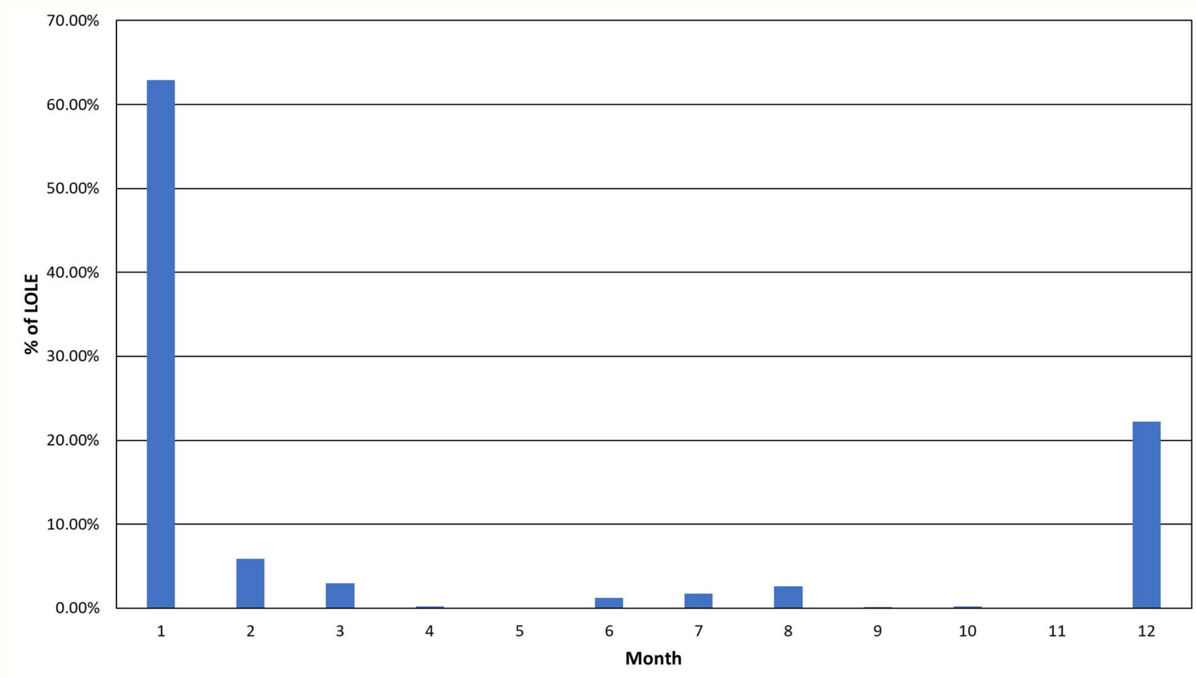


Figure ES 1. Monthly Breakdown of LOLE

Additionally, an analysis of summer reliability was conducted even though winter is still the binding season. It was found that a summer reserve margin of 15% would result in approximately 0.015 LOLE so because of this, it is recommended that a summer reserve margin of 15% be maintained as a secondary constraint to the 20.1% winter reserve margin.

The following sensitivities were also evaluated to test the robustness of the base case PRM:

1. Islanded Base Case (i.e., no market assistance)
2. Islanded Base Case with optimized maintenance
3. Cold Weather Load response lower than base case assumptions
4. Cold Weather Load response higher than base case assumptions

The table below shows the results of each of these sensitivities.

Table ES 1. PRM Results

	2026
Base Case w/Market	20.1%
Base Case Island	43.4%
Optimized Maint Island	37.0%
High Load Response	22.2%
Low Load Response	16.2%

As indicated by the results in the table, there is a significant benefit to the interconnected DESC system, with the market providing nearly a 23% benefit to the reserve margin requirement compared to the Base Island case. The high and low load response sensitivities resulted in approximately +2% and -4% reserve margin adjustments, respectively.

ELCC RESULTS

The ELCC of a renewable resource/portfolio represents the amount of dependable capacity that can be counted on by the renewable resource/portfolio for resource adequacy purposes. The ELCC is determined by finding the amount of additional load that can be served by the renewable resource/portfolio without adversely affecting system reliability as compared to a system without the renewable resource/portfolio. The ELCC is represented as a percent of nameplate capacity and is calculated by dividing the amount of additional peak load served by the nameplate capacity of the additional renewable resource/portfolio.

The table below shows the various levels of solar and BESS penetrations, as well as combined portfolios of solar and BESS, for which ELCCs were calculated. The analysis was performed this way to ensure any synergistic value of solar and storage are captured in the study.

Table ES 2. ELCC Scenarios

	Battery(MW)				
Solar(MW)	**100**	**150**	**400**	**650**	**900**
1,335		x	x	x	x
1,435	x	x			
1,935	x		x		
2,435	x			x	
2,935	x				x

The tables below show the average winter ELCC for the incremental solar portfolio and then the average and marginal ELCC for the incremental storage portfolio for their respective dispatch patterns. The values in Table ES 3 and ES 4 represent the combined portfolio results capturing any synergistic value found between the two resources.

Table ES 3. Winter Solar ELCC Results

Incremental Solar(MW)	**Solar Average ELCC(%)**
100	2.7%
600 (+500)	0.7%
1,100 (+500)	0.5%
1,600 (+500)	0.5%

The storage analysis was conducted using two approaches. The first assuming that DESC has full control of the battery on cold winter days and will operate the battery conservatively whereas the economic arbitrage method assumes that DESC does not have control of the storage resource and that it will be scheduled without perfect knowledge of the forced outages on the system.

Table ES 4. Winter Storage ELCC Results

Incremental Storage(MW)	**4 Hour Storage Average ELCC(%)**	**4 Hour Storage Average ELCC(%)**	**4 Hour Storage Marginal ELCC(%)**	**4 Hour Storage Marginal ELCC(%)**
	Conservative Operations on Extreme Days	**Assumes Economic Arbitrage**	**Conservative Operations on Extreme Days**	**Assumes Economic Arbitrage**
50	100%	93%	100%	93%
300	100%	91%	100%	90%
550	99%	88%	98%	85%
800	95%	86%	88%	80%

Based on the results, a 20.1% winter reserve margin meets the 1 day in 10 year standard and is appropriate for planning purposes. Neighbor assistance plays a vital role in reliability across the year and has been included in this study. While there is uncertainty surrounding extreme cold weather load response, allowing the winter reserve margin to drop below 20% is likely to provide reliability levels lower than DESC's 1 day in 10 year reliability standard.

INTRODUCTION

The purpose of this document is to report on the results of a study performed by Astrapé Consulting to determine the Planning Reserve Margin (PRM) necessary for Dominion Energy South Carolina (DESC) to maintain a Loss of Load Expectation (LOLE) of 0.1 days/year or the equivalent of the common industry practice of one loss of load event in 10 years. The study examined the reserve margin requirements for a single study year, 2026.

In addition, this document will also report on the results of a study to determine the Effective Load Carrying Capability (ELCC) of the portfolio of solar resources expected to be installed on the DESC system.

STUDY FRAMEWORK

This study was performed using the Strategic Energy & Risk Valuation Model (SERVM) and its associated study framework. The SERVM framework combines an hourly (i.e., 8760-hour) production cost model coupled with Monte Carlo outage simulation and comprehensive scenario management that considers load and weather uncertainty in order to determine key reliability parameters such as Loss of Load Expectation (LOLE). The following describes the key parameters and uncertainties that are considered and how they are applied within the study framework.

WEATHER UNCERTAINTY

To account for weather uncertainty, SERVM performs hourly production cost simulations using multiple load shapes representing historical weather years. The uncertainties that are modeled for each modeled weather year include load shapes, renewable profiles, hydro availability, and temperature impacts on thermal resources. Load shapes for each weather year are developed to represent the expected future load response to the historical weather. For example, a 1990 weather year represents how loads would respond if 1990 weather were to repeat itself in the future. These load shapes are then scaled so that the average of the peak demands from the last 30 weather year load shapes (1992-2021) equals the study year weather normal peak load forecast. Similarly, renewable profiles and hydro schedules are developed to represent the expected future availability associated with the historical weather profile. For purposes of this study, 42 weather year scenarios were simulated representing weather conditions for the years 1980-2021.

ECONOMIC LOAD FORECAST ERROR

Economic Load Forecast Error represents the potential error in the weather normal peak load forecast associated with uncertainty in economic forecasts. Using the Office of Congressional Budget's historical forecasts for Gross Domestic Product (GDP), it is possible to predict both the magnitude and probability of error in the forecast of the GDP economic indicator 3, 4, or 5 years out into the future. This probability of error can then be converted into a Load Forecast Error (LFE). For purposes of this study, 5 LFE scenarios were chosen. These are described in the Model Development section of this document. Each of the 42 weather year scenarios are combined with each of the 5 LFE scenarios to create 210 unique load scenarios, or "cases".

MONTE-CARLO OUTAGE ITERATIONS

SERVM uses monte-carlo techniques to simulate generator outages. Multiple hourly production cost simulations are run for each of the 210 load cases. With each outage iteration, random monte-carlo draws are made to determine the outage profile associated with that scenario. For purposes of this study, 80 outage draw iterations were made for each case. The specifics associated with how these outages were modeled are detailed in the Model Development section of this document.

As shown in the figure below, the SERVM uncertainty framework used for this study required at least 16,800 (8760-hour) production cost simulations for a single analytical run of the DESC system and its first tier neighbors.

42 **Weather Years** (Equal Probability)	x	**5** **LFE Points** (Associated Probabilities)	=	**210** **Load Scenarios** (Associated Probabilities)
210 **Load Scenarios**	x	**80** **Unit Outage Draws**	=	**16,800** **8760 Hour Simulations**

Figure 1. SERVM Uncertainty Framework

The Study Methodology section of this document describes the numerous "analytical runs" required to perform the reserve margin analysis, its associated sensitivities, as well as the ELCC analysis.

MODEL DEVELOPMENT

The SERVM data model utilized for this study was based upon load and resource profiles for the DESC Balancing Authority Area (BAA) and its immediate first tier interconnected BAAs, including the BAAs associated with Southern Company (SOCO), Duke Energy Carolinas (DEC), Duke Energy Progress (DEP), and Santee Cooper (SC). The figure below shows the configuration of the study model with its associated transmission interface connections using a pipe and bubble configuration.

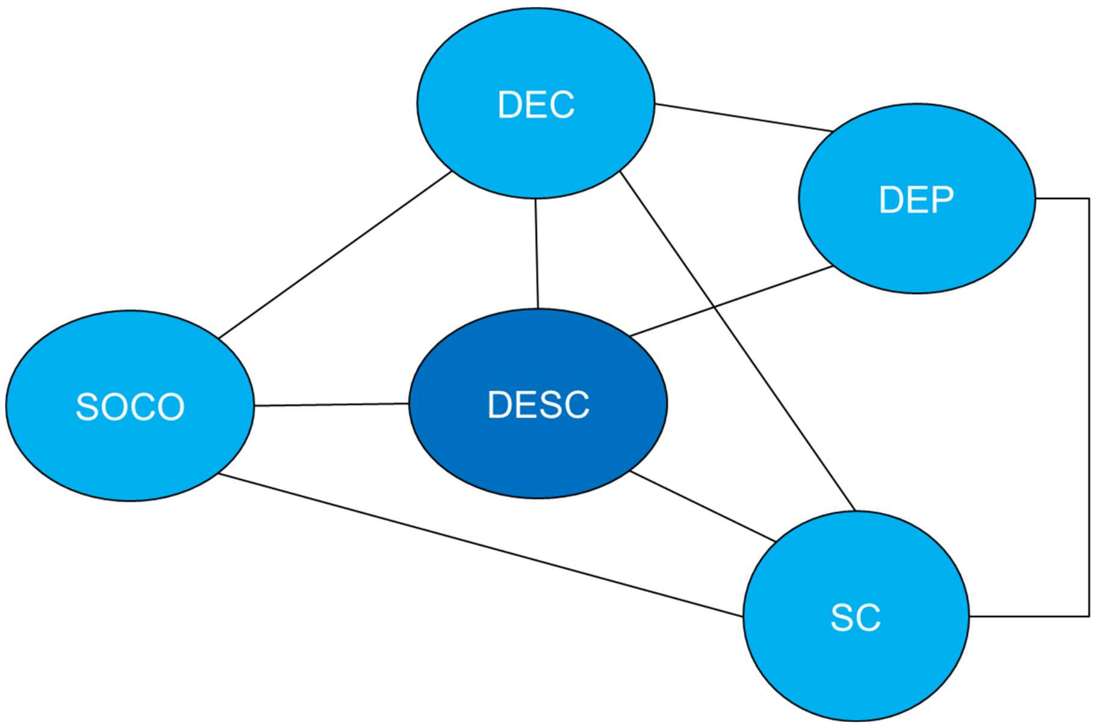


Figure 2. Study Model Configuration

BASIS FOR MODEL DEVELOPMENT

The basis for the SERVM model used in this study was the data included in Astrapé Consulting's Eastern Interconnection Database (EIDB) with revisions to the DESC region per data provided directly by DESC. Astrapé's EIDB was developed and is maintained using publicly available data from sources such as the Energy Information Authority (EIA) Form 860, available documents from the North American Reliability Corporation (NERC), various publicly available Integrated Resource Plans (IRPs), FERC Forms, and the like.

The following provides the specifics of the DESC data as provided by DESC for purposes of this study.

PEAK DEMAND FORECAST

For this study, the 2026 peak demand forecast represented the gross load (i.e., before any reductions due to curtailable load or renewable load injections) reduced for anticipated Energy Efficiency (EE) impacts. The summer and winter peak demand forecasts as provided by DESC are shown in the figure below.

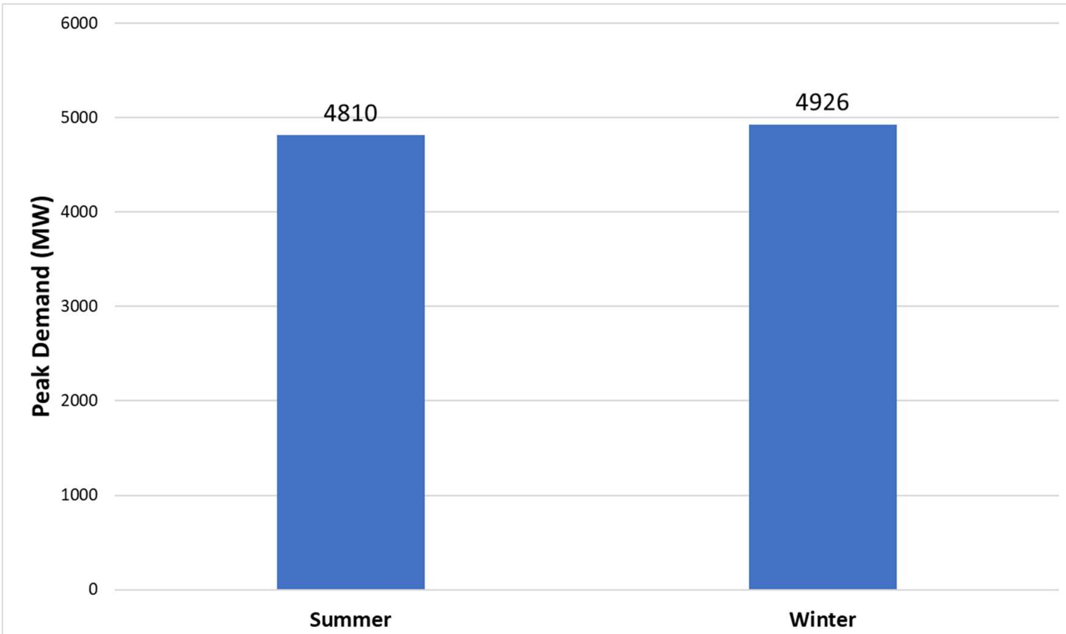


Figure 3. Peak Demand Forecast

LOAD MODELING

As described in the Study Framework subsection of the Introduction section above, load shapes were developed for each of the 42 study years 1980-2021. These load shapes were developed based on trends and relationships between load and weather for the years 2017-2021.

The five historical load shapes trended using a neural network that was trained using weighted hourly historical temperatures from the National Oceanic and Atmospheric Administration (NOAA) and other key variables. The following NOAA weather stations along with the indicated weighting were used to develop the temperature variables. Gaps in the weather data were filled using adjusted weightings of the remaining stations.

Table 1. NOAA Weather Stations and Weightings

Station	Weighting
Columbia	50.0%
Charleston	50.0%

In addition to temperature, the neural net was provided with training variables that included day of week, hour of day, hour of week, 8-hour rolling average temperature, 24-hour rolling average temperature, and 48-hour rolling average temperature. "Networks" were created for Winter, Summer, and Shoulder periods. These trained networks were then applied to the NOAA weather data for the historical years 1980-2021 to develop synthetic load shapes for each of the 42 weather years.

Since the 42 years of historical weather data contains temperature data outside the range of that contained in the 5-year historical load set used to train the neural networks, extreme peaks were determined using peak load regressions developed outside the neural network. Peak load regressions were developed for summer afternoon, winter morning, and winter afternoon periods.

The final load shapes were a combination of those hours developed using the neural net and those developed using the peak load regressions. The synthetic load shapes were then quality checked against the actual historical shapes to ensure their validity.

The figure below shows a plot of the daily peak loads as a function of either the daily max or daily min temperature as appropriate. The figure compares the 5 years of historical data with the 41 years of synthetic data.

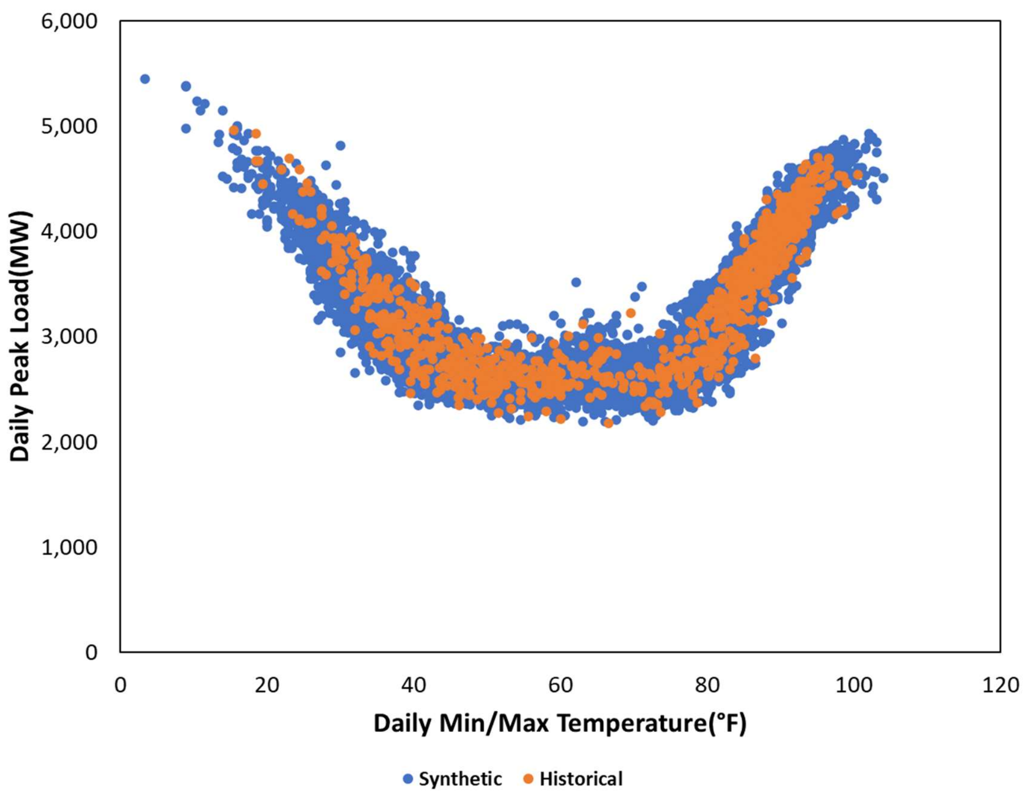


Figure 4. Synthetic vs. Historical Daily Peak Loads

The development of the 42 synthetic load shapes results in a diverse set of annual peak loads. Within SERVM, these shapes will be scaled such that the average of the last 30 annual peak loads (1992-2021) will equal the weather normal peak load for both summer and winter. The figures below show the summer and winter peak load variance resulting from the 41 synthetic load shapes. The variance is shown in terms of its divergence from the weather normal peak load on a percentage basis.

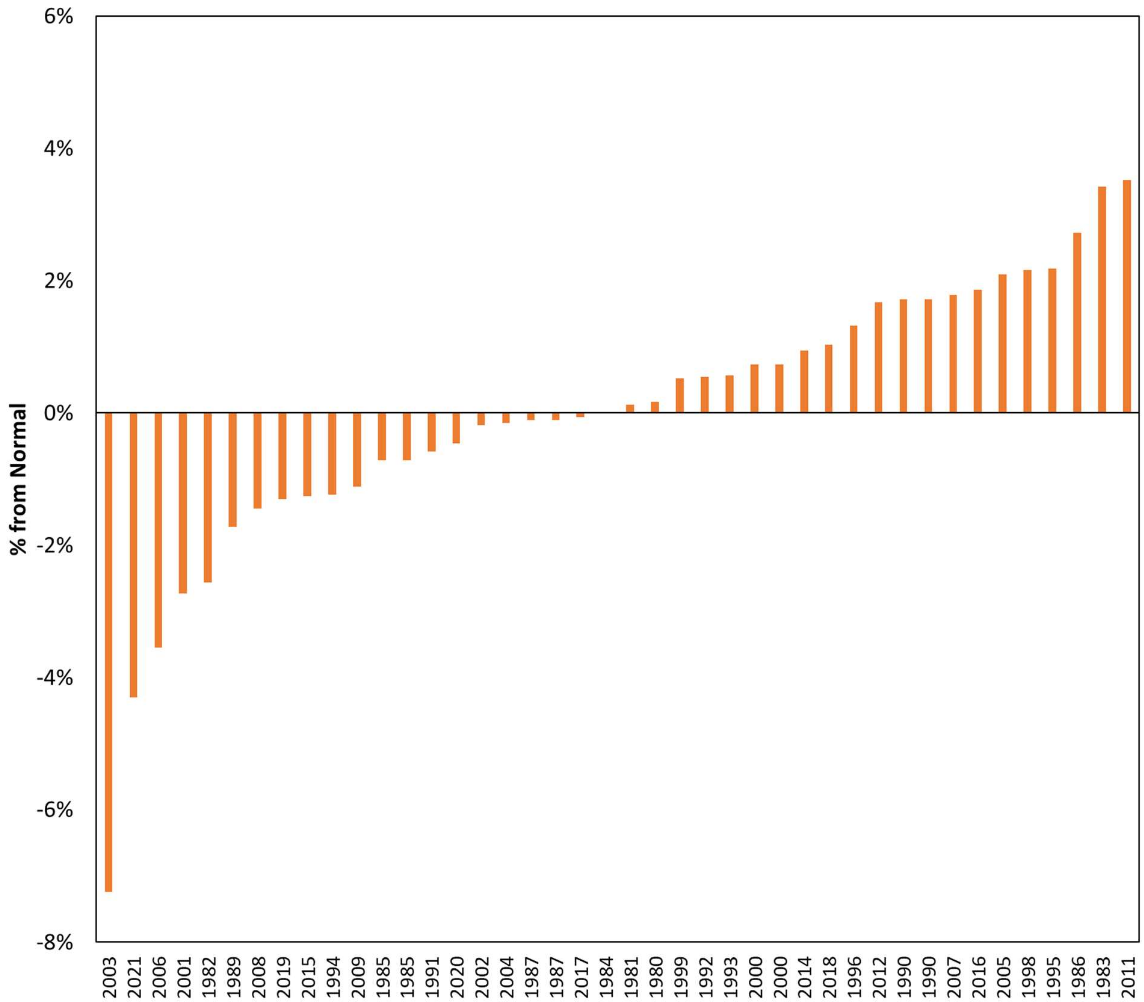


Figure 5. Summer Peak Load Variance

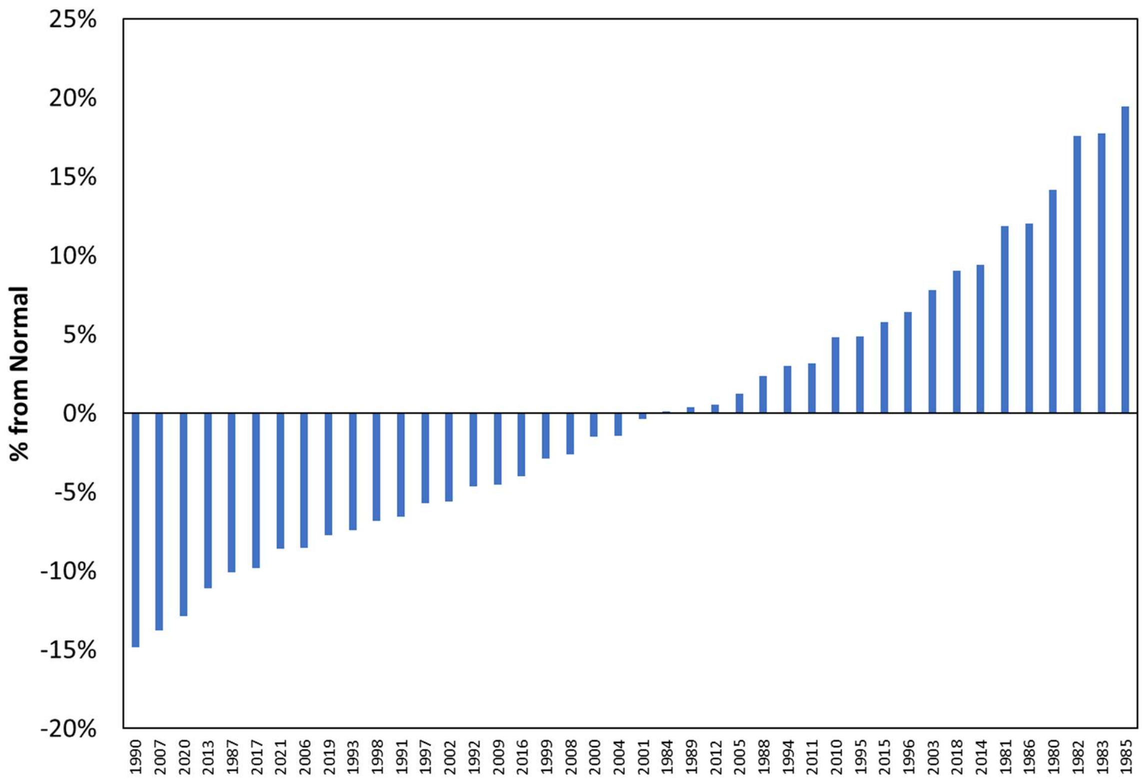


Figure 6. Winter Peak Load Variance

ECONOMIC FORECAST ERROR

As described in the Study Framework subsection of the Introduction section of this document, five Load Forecast Error (LFE) multipliers with their associated probabilities were applied to each of the 42 historical load shapes. The LFE multipliers simulate the expected probability that the peak demand forecast would be missed because of errors in the forecast of national economic indicators. The multipliers were developed by looking at the historical error in the 4-year out forecast GDP assuming a peak demand sensitivity to changes in GDP of 0.4% per 1% change in GDP. The set of LFE multipliers along with their probability of occurrence used in this study are shown in the table below with a graphic representation in the figure that follows.

Table 2. LFE Model

LFE	Probability
-4%	10.4%
-2%	23.3%
0%	32.5%
2%	23.3%
4%	10.4%

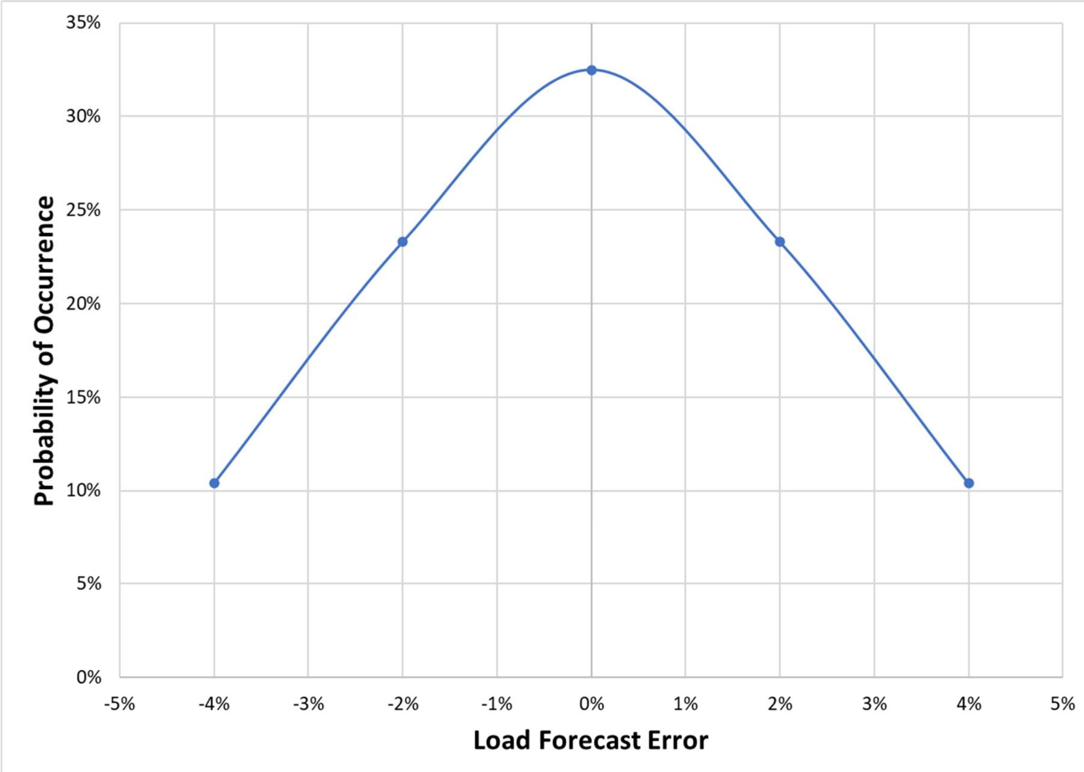


Figure 7. LFE Model

CONVENTIONAL RESOURCE MODELING

Resources for the first tier BAAs were developed using publicly available information. Resources for DESC were developed using data provided by DESC as outlined in the subsections below.

GENERATING CAPACITY

The following table shows the list of conventional resources and their corresponding summer and winter generating capabilities available to DESC for the 2026 study year.

Table 3. DESC Conventional Resource Capacities

Unit Name	Unit Category	Summer Capacity	Winter Capacity
CEC CC	GCC	559	638
Cope ST1	Coal	415	415
Jasper CC	GCC	895	979
LT CT 1	CT- Gas	48	48
LT CT 2	CT- Gas	42	42
LT CT 3	CT- Gas	90	90
LT CT 4	CT- Gas	20	20

LT CT 5	CT- Gas	40	40
McMeekin 1	GCC	125	125
McMeekin 2	GCC	125	125
Parr CT1	CT- Gas	40	48
Parr CT2	CT- Gas	40	48
Urquhart 3	Gas	95	96
Urquhart CC	GCC	464	484
V C Summer 1	Nuclear	647	661
Williams LM6000	CT- Gas	40	48
Williams ST1	Coal	605	605

To model the transition from summer ratings to winter ratings, technology curves were developed for each unit that adjusted the maximum capacity of the resource based on ambient temperature. The figure below shows an example technology curve based on the CEC CC. Other curves are similar.

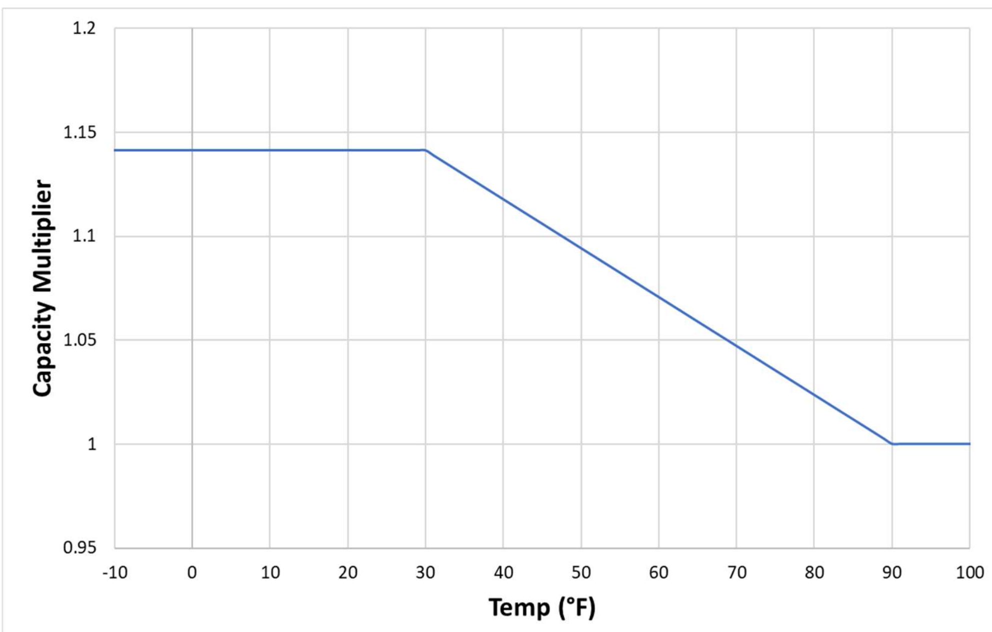


Figure 8. Example Technology Curve

OUTAGE MODELING

Outage modeling consisted of three primary types of outages, planned maintenance, unplanned maintenance, and forced outages.

SERVM can model planned maintenance, often called planned outages (PO), as either discrete schedules or an annual rate in percent of hours. If modeled as a PO rate, SERVM schedules planned maintenance in seasons where there would not typically be an expectation of reliability concerns. This determination is made by looking at all available weather year load shapes and developing a schedule that is least likely to cause reliability concerns. Thus, while it may be generally expected that planned maintenance will not create reliability issues, there may be some weather years in which that is not the case.

Planned maintenance rates were determined from NERC GADS data provided by DESC and then reviewed by experts at DESC for any potential adjustments. For units that did not have GADS data, a generic maintenance rate of 5% was assumed. The figure below shows the final planned maintenance rates modeled for the DESC conventional units.[1]

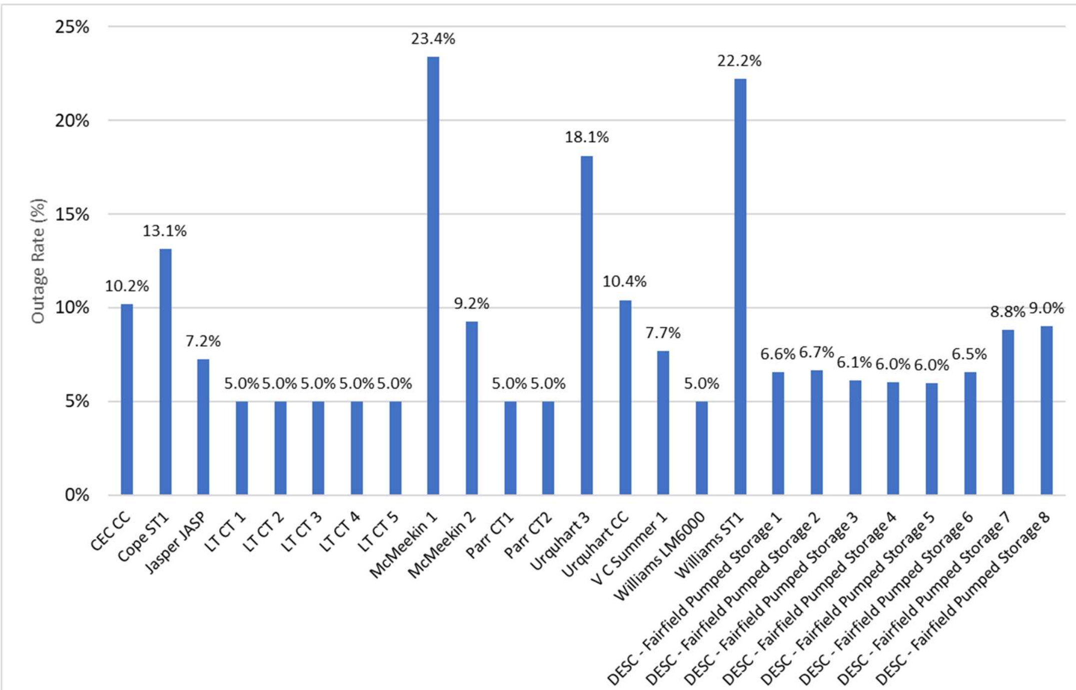


Figure 9. DESC Planned Maintenance Rates

See the discussion below on forced outages for landfill gas (LFG) and biomass modeling.

SERVM also models unplanned maintenance, often referred to as Maintenance Outages (MO), as a rate. SERVM uses these rates to determine the amount of time that a resource should be offline due to maintenance outages and attempts to schedule those hours during off-peak periods. However, because SERVM models these outages during hours without reliability risk, they have no material impact on the reserve margin study. Thus, no unplanned maintenance outages were modeled for this study.

[1] In addition to the conventional units, the chart includes planned maintenance rates for the 8 pumped storage hydro facilities (discussed later in this report).

SERVM models forced outages using multiple sets of time to fail (TTF) and time to repair (TTR) inputs for both full and partial outages. Each resource has its own set of TTF and TTR inputs that are used to establish that resource's equivalent forced outage rate (EFOR). Using monte carlo techniques, a TTF value is chosen randomly for each generating unit. That resource is then allowed to operate until it reaches the TTF threshold, at which point it is forced offline. Once it is forced offline, a TTR value is chosen randomly to determine how long the resource will be unavailable. That resource remains offline until it reaches the TTR threshold, at which point it is once again made available and a new TTF variable is chosen for the resource.

The TTF and TTR values for DESC were developed using five years of historical NERC GADS data and consultation with DESC experts and internal planning models. The figure below shows the final modeled EFOR rates by unit.

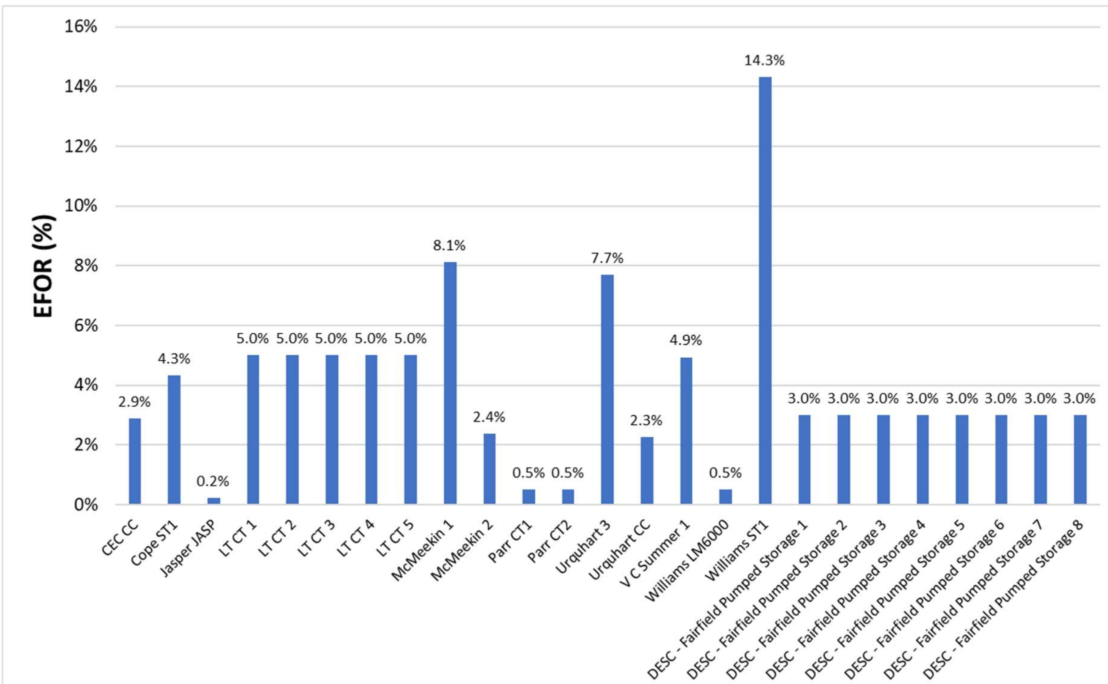


Figure 10. DESC EFOR Rates

OTHER CONVENTIONAL DATA

Other conventional resources data provided by DESC included minimum capacities, minimum uptime, minimum downtime, and ramp rates.

SOLAR RESOURCE MODELING

SERVM models renewable resources as an hourly profile for each weather year. For purposes of this study, one location in each South Carolina county was chosen to create a generic fixed and tracking profile. All solar projects were then mapped to the county in which the project exists. A total of 46 solar projects were modeled for the 2026 study year representing approximately 1,336 MW which includes current projects under development and with a commitment to DESC. Three of the projects were hybrid projects containing on site battery storage. To create the weather year profiles, irradiance data for each location was downloaded from the National Renewable Energy Laboratory (NREL) National Solar Radiation Database (NSRDB) Data Viewer for the years 1998 to 2020.[2] The data obtained from the NSRDB Data Viewer was input into NREL's System Advisor Model (SAM)[3] for each year and location to generate the hourly solar profiles based on the solar weather data for fixed and tracking solar plants. Solar profiles for the other weather years were selected by using the daily solar profiles from the day that most closely matched the peak load for the DESC load out of all the days +/- 3 days of the source day. The profiles for the specific downloaded years (1998 to 2020) came directly from the solar shape output data from SAM. The profiles were then scaled and assigned an inverter loading ratio such that across the 42 weather years each project would achieve the desired capacity factor as specified by DESC.

The three hybrid solar projects have associated battery storage with capacity, storage, and maximum combined solar plus battery capacity values and operating characteristics as shown in the table below.

Table 4. Hybrid Solar Battery Capacities

Facility	Battery Capacity	Battery Storage	Combined Solar & Battery Capacity
Eastover Hybrid	18 MW	4 Hrs	73.6 MW
Lone Star Hybrid	66 MW	3 Hrs	66 MW
Wolf Pit Branch Hybrid	15.5 MW	4 Hrs	62 MW

Each of these batteries were modeled to charge using the output of the connected solar facility, with a 3% forced outage rate.

HYDRO RESOURCE MODELING

DESC has eight 72 MW Pumped Storage Hydro (PSH) units at the Fairfield PSH facility and four conventional hydro facilities at Neal Shoals, Parr, Saluda, and Stevens Creek. The PSH Facilities were modeled as individual storage units with characteristics as shown in the table below.

Table 5. PSH Characteristics

Characteristic	Value
Max Capacity	72 MW
Min Capacity	10 MW
Pond Size	6.875 Hours
Outage Rate	3%

[2] https://maps.nrel.gov/nsrdb-viewer/
[3] https://sam.nrel.gov/

The conventional hydro units were aggregated into two resources – an aggregate resource representing the normal scheduling of hydro on a day-by-day basis and an emergency hydro unit that represents the ability to deviate from the hydro schedule on an emergency basis. The size of the aggregate schedulable unit varies by month and weather year based on water availability as described below. The emergency hydro represents approximately 53 MW of schedule deviation under emergency conditions.

SERVM models hydro facilities by scheduling available hydro energy to shave the daily net peak load using four different parameters for each month for each weather year. Those parameters include:

1. Monthly total energy output,
2. Daily scheduled maximum output,
3. Daily scheduled minimum output, and
4. Monthly maximum scheduled output.

The daily minimum hydro dispatch is scheduled at the minimum net load hour of the day, and the daily maximum hydro is scheduled at the maximum net load hour of the day, and the monthly maximum hydro is scheduled at the max load hour of the month, all while observing the monthly total energy output constraint. The monthly maximum scheduled output sets the available hydro capacity for that month, which varies by weather year based on availability of water.

To develop these parameters, available hydro energy data from 1980 to 2021 was collected from the EIA Form 923[4] and actual hourly hydro data was provided by DESC for the years 2017 to 2021. Using this data, average daily minimum and maximum dispatch levels, the total monthly energy, as well as the monthly maximum dispatch levels were identified from the historical hourly data and a regression of each was formed. These regressions were then applied to the historical monthly energy data obtained from EIA forms. The resulting parameters were then applied to the corresponding weather year as appropriate.

The figure below show the result of the regression analysis for the DESC hydro facilities.

[4] https://www.eia.gov/electricity/data/eia923/

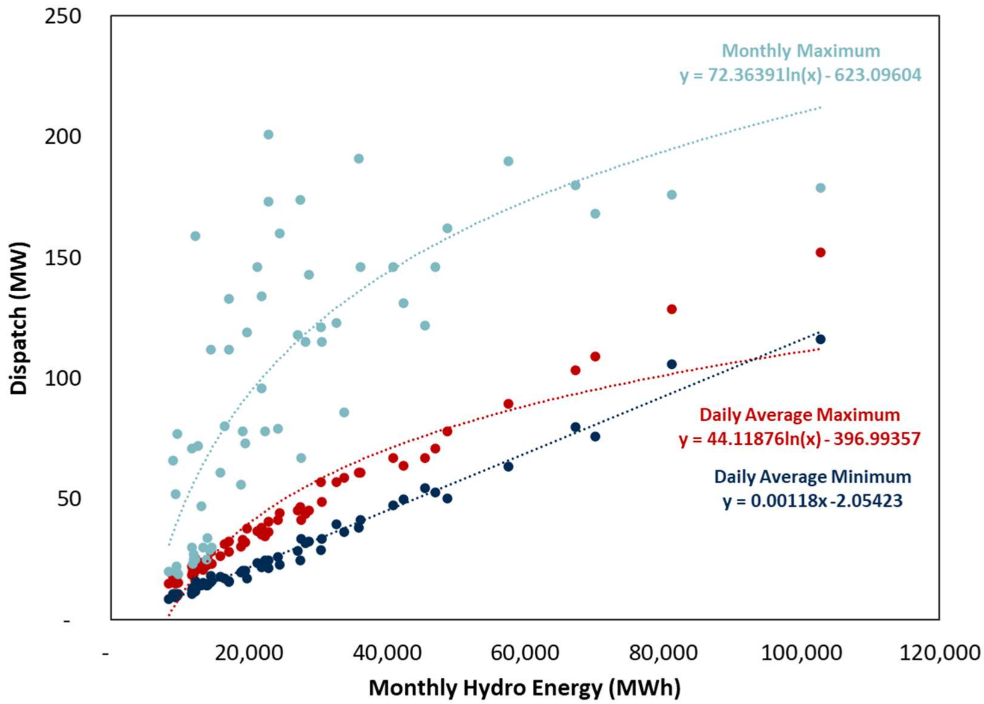


Figure 11. Hydro Regression Results

The figure below shows the available hydro energy by weather year for the DESC hydro facilities.

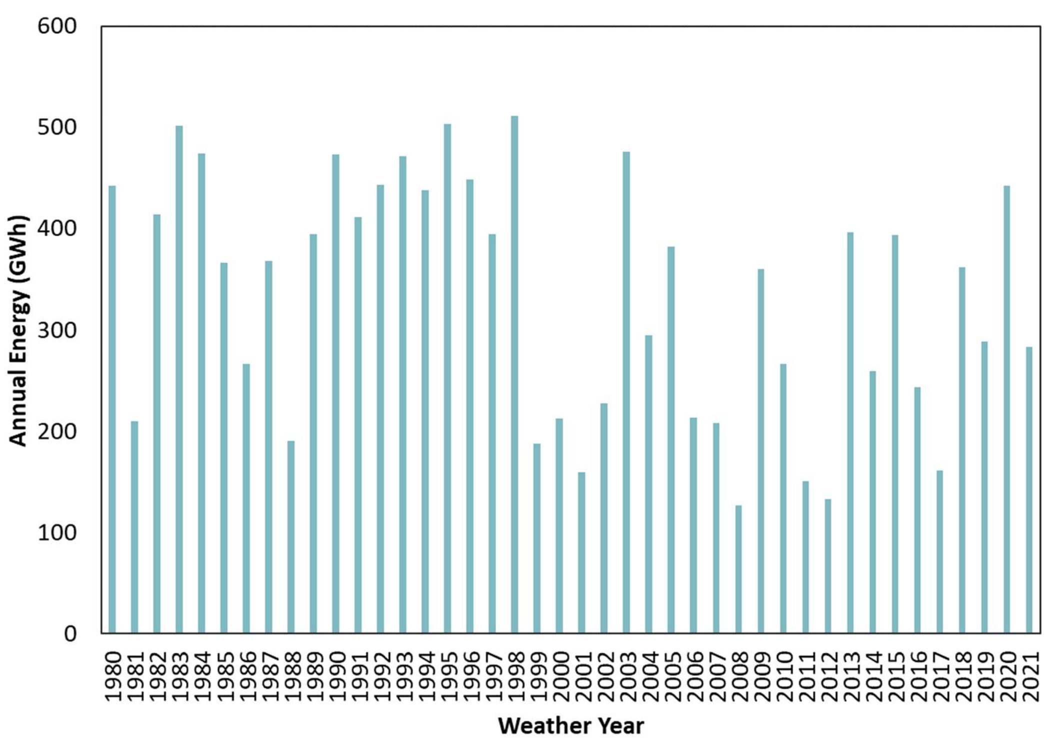


Figure 12. Hydro Energy by Weather Year

The figure below shows the resulting monthly available capacity for the DESC hydro facilities.

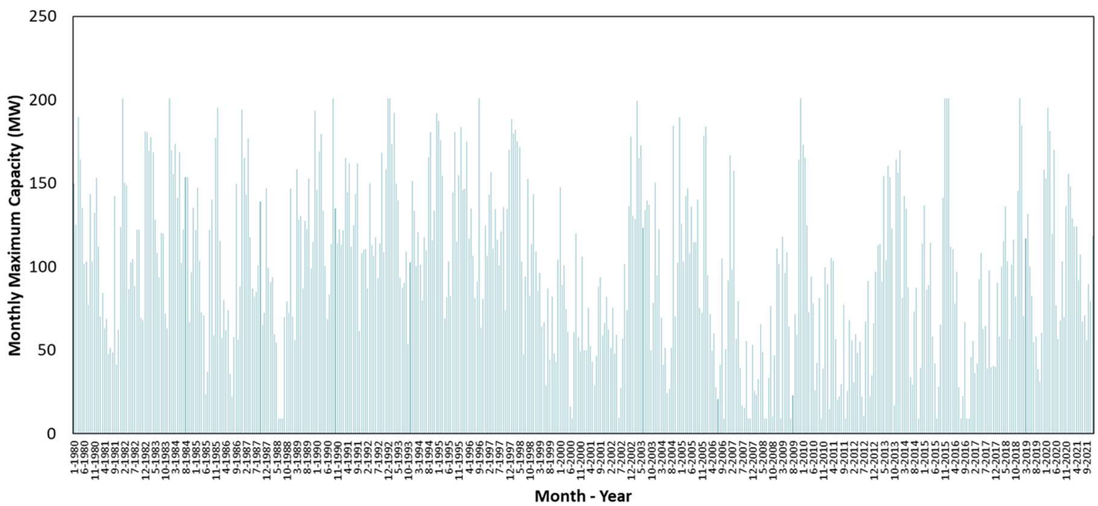


Figure 13. Monthly Hydro Capacity

DEMAND RESPONSE MODELING

For purposes of this study, Energy Efficiency (EE) is modeled as a reduction in load. All load shapes and peak demand forecasts were developed net of EE.

Although DESC has a number of demand response programs, for purposes of this study, they were aggregated into three resources, interruptible customers (196 MW in summer and 193 MW in winter), stand by generators (11 MW in both summer and winter), and AMI (69 MW in the winter). The interruptible customers were modeled with the following characteristics:

Table 6. Interruptible Customer Characteristics

Characteristic	Value
Yearly Limit	300 Hrs
Monthly Limit	50 Hrs
Daily Limit	8 Hrs
Max Daily Calls	1
Max Weekly Calls	3
Max Monthly Calls	10

The interruptible resource was modeled with a curtail price that initiated curtailment just before the operation of stand by generation. The stand-by generation was modeled with no limitations other than it could only be called to avoid a load shed event.

RESOURCE CAPACITY MIX

The model of the system described above resulted in a system with the mix of resources shown in the figure below. All values are in MW representing summer capacity values. Hydro represents the approximate summer capacity schedulable and solar resources are shown with nameplate values. Hybrid battery capacity is not shown in the figure as it is assumed to be part of the solar capacity.

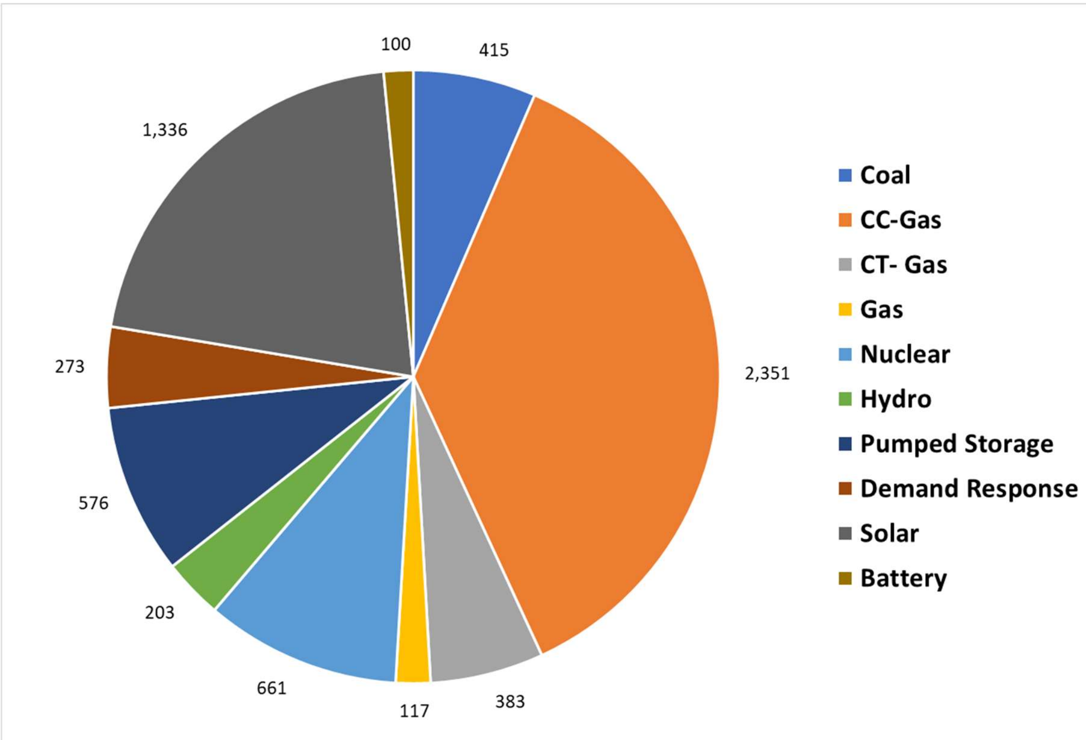


Figure 14. Resource Capacity Mix (Winter Ratings)

Battery capacity is all associated with hybrid solar-battery facilities.

ANCILLARY SERVICES MODEL

The ancillary services model included as part of this study included the modeling of regulating reserves, contingency reserves spinning (spinning reserves), contingency reserve supplemental (non-spinning reserves). SERVM will attempt to commit the system to maintain all ancillary services requirements. However, spinning and non-spinning reserves would be allowed to deplete to zero to avoid a load shedding event. Regulating reserves would be maintained during load shedding events. Based on information provided by DESC, the following baseline set of operating reserves were modeled.

Table 7. Base Ancillary Services Requirements

Reserve Component	Requirement (MW)
Regulating Reserves	45
Spinning Reserves	113
Non-Spinning Reserves	113

In addition to the base ancillary services requirement, DESC provided guidance regarding additional load following reserves to be maintained, if available, to help manage solar integration. These varied by month and were only applied to daytime periods when solar output is expected. The table below shows the monthly load following target modeled in the study.

Table 8. Load Following Targets

Month	LF Target (MW)
January	515
February	605
March	660
April	666
May	655
June	598
July	565
August	545
September	569
October	555
November	508
December	424

TRANSMISSION MODEL

Note: the information contained within this section of the report is confidential and subject to Critical Energy/Electric Infrastructure (CEII) restrictions. The import and export values used for this study were taken directly from the SERC Near Term Working Group 2021 Summer and 2021-2022 Winter Reliability Studies which is confidential. The import limits modeled into DESC were high in magnitude and were not seen as a significant constraint in the study.

MARKET ASSUMPTIONS

As SERVM performs its 8760-hour production cost simulation, it makes a determination each hour as to the availability and price of potential market transactions between BAAs. This determination is made through development of both a day ahead and an hourly market price for each region that is based on a combination of an energy price and a scarcity price according to the equation

MP = MEP + ORDC

Where
MP= Market Price
MEP= Marginal Energy Price (a.k.a, the marginal dispatch price), and
ORDC=the Operating Reserve Demand Curve price.

The ORDC price provides a scarcity price signal based on the amount of remaining undispatched operarating reserves.

SERVM allows economic transactions based on each region's resulting market price subject to transmission constraints.

STUDY METHODOLOGY

The two objectives of this study were to (a) establish the PRM for the DESC system and (b) determine the ELCC for various penetrations of solar and battery energy storage system (BESS) resources. The sections below describe the approach for each of these two objectives.

ESTABLISHING MW ADJUSTMENT

The PRM for the DESC system was determined for the 2026 study year which should be reasonably representative of existing and near future PRM.

To determine the PRM, expansion CTs were iteratively added to the base case system until the annual LOLE reached 0.1 days/year. This requires making multiple runs with differing amounts of expansion CTs (e.g., 1 CT, 2 CTs, etc.) and trending the resulting LOLE so that the 0.1 LOLE point can be interpolated. The result of this extrapolation was the MW adjustment necessary to achieve 0.1 LOLE. This analysis was performed on both an islanded basis as well as a regional basis that included the DESC first tier BAAs.

Converting the results of this analysis into a resulting PRM required the establishment of an ELCC for the existing solar and storage resources as described in the next subsection below. The final determination of the PRM (in %) was determined as follows:

PRM = [(Existing Capacity[5] + Adjustment Capacity) / Peak Load – 1] * 100.

DETERMINING ELCC

To calculate the existing portfolio ELCC value, the following steps were taken.

1. Remove all renewables and storage from the DESC system (LOLE will increase above 0.1 days/year).
2. Add back perfect capacity until system returns to 0.1 days/year LOLE.
3. Divide the amount of perfect capacity added by the nameplate capacity of the resources removed.
4. Prorate the individual technologies to equate to the total portfolio value.

To calculate the incremental solar and storage ELCC values, the following steps were taken.

1. Add the portfolio(s) of solar and storage to the DESC system (LOLE will decrease above 0.1 days/year) to capture any of the synergistic value of the technologies.
2. Add back load until system returns to 0.1 days/year LOLE.
3. Divide the amount of negative load added by the nameplate capacity of the resources added.
4. Prorate the individual technologies to equate to the total portfolio value.

[5] For PRM calculation purposes, demand response and hydro are treated as a resource, and solar and storage resources are applied at the appropriate ELCC values.

STUDY RESULTS

The following outlines the results of the base case PRM analysis as well as the ELCC analysis.

BASE CASE ISLAND

As described in the Study Methodology section above, the islanded DESC system PRM was evaluated in 2026 by simulating the system with the addition of the marginal capacity to find the winter reserve margin necessary to achieve 0.1 days/year LOLE. The table below shows different winter reserve margin levels and their associated reliability metrics. The island scenario is driven largely by forced outages and planned maintenance since there is no market assistance at all even during mild weather patterns. LOLE can occur almost any time of the year which is why the required reserve margin is so high.

Table 9. Islanded PRM Simulated Results

Winter Reserve Margin(%)	Summer Reserve Margin(%)	LOLE (events per year)	EUE(MWh)	LOLH(hours per year)	LOLP
35.0%	38.6%	0.674	1010	3.118	0.036%
36.0%	39.6%	0.574	856	2.648	0.030%
37.0%	40.6%	0.482	714	2.215	0.025%
38.0%	41.7%	0.398	585	1.820	0.021%
39.0%	42.7%	0.322	467	1.462	0.017%
40.0%	43.7%	0.254	363	1.142	0.013%
41.0%	44.7%	0.193	270	0.859	0.010%
42.0%	45.8%	0.141	190	0.614	0.007%
43.0%	46.8%	0.096	123	0.406	0.005%
44.0%	47.8%	0.059	67	0.235	0.003%
45.0%	48.8%	0.030	24	0.102	0.001%

The following figure shows the DESC annual LOLE for 2026 as a function of winter reserve margin.

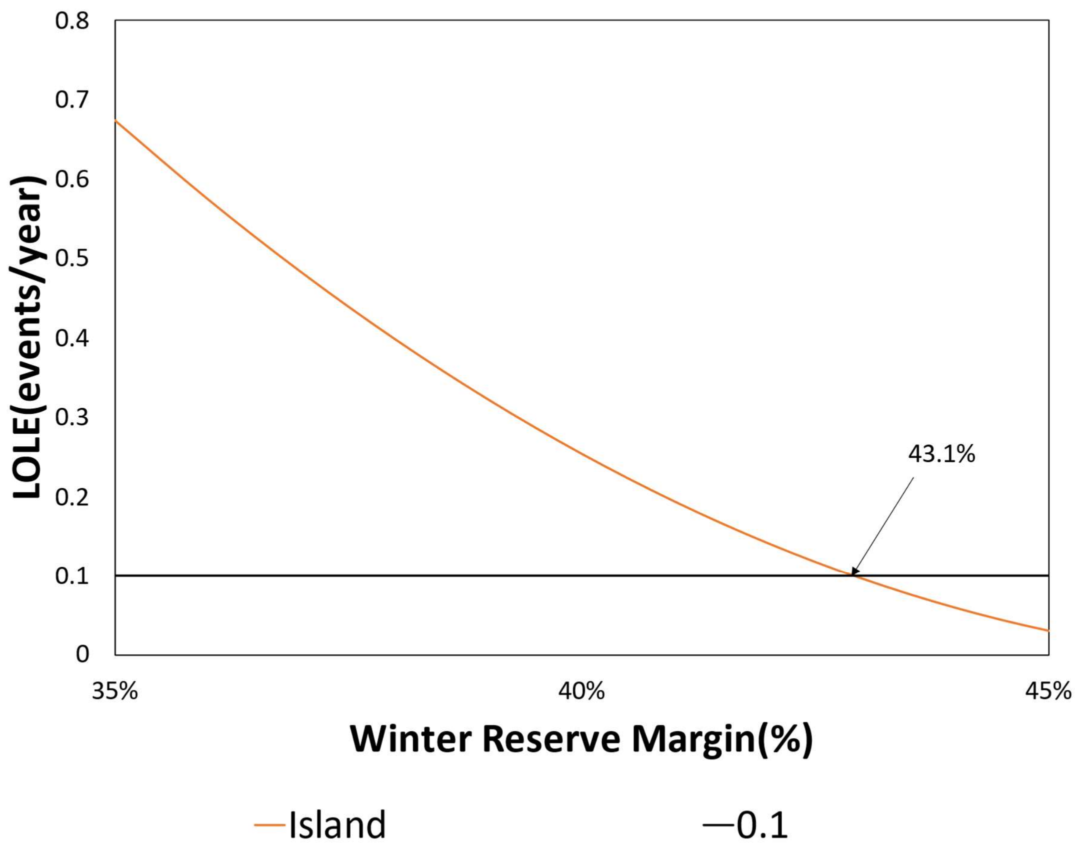


Figure 15. Islanded LOLE as a Function of PRM

BASE CASE INTERCONNECTED PRM

The table below shows the scenarios simulated as well as the resulting LOLE for the DESC interconnected system that included first tier BAAs.

Table 10. Interconnected PRM Simulated Results

Winter Reserve Margin(%)	Summer Reserve Margin(%)	LOLE (events per year)	EUE(MWh)	LOLH(hours per year)	LOLP
5.0%	7.9%	0.310	443	0.877	0.010%
6.0%	8.9%	0.293	407	0.819	0.009%
7.0%	9.9%	0.277	374	0.764	0.009%
8.0%	10.9%	0.261	341	0.710	0.008%
9.0%	12.0%	0.245	311	0.659	0.008%
10.0%	13.0%	0.230	282	0.609	0.007%
11.0%	14.0%	0.215	254	0.562	0.006%
12.0%	15.0%	0.200	229	0.516	0.006%
13.0%	16.1%	0.187	204	0.473	0.005%
14.0%	17.1%	0.173	181	0.432	0.005%
15.0%	18.1%	0.160	160	0.393	0.004%
16.0%	19.1%	0.148	140	0.355	0.004%
17.0%	20.2%	0.136	122	0.320	0.004%
18.0%	21.2%	0.124	106	0.287	0.003%
19.0%	22.2%	0.113	91	0.256	0.003%
20.0%	23.2%	0.103	77	0.227	0.003%
21.0%	24.3%	0.093	65	0.200	0.002%
22.0%	25.3%	0.083	55	0.175	0.002%
23.0%	26.3%	0.074	46	0.152	0.002%
24.0%	27.3%	0.065	39	0.131	0.001%
25.0%	28.4%	0.057	33	0.113	0.001%
26.0%	29.4%	0.049	29	0.096	0.001%

The following figure shows the DESC annual LOLE for 2026 as a function of winter reserve margin[6].

[6] Winter ELCC for the solar resources per the ELCC results calculated during the ELCC analysis.

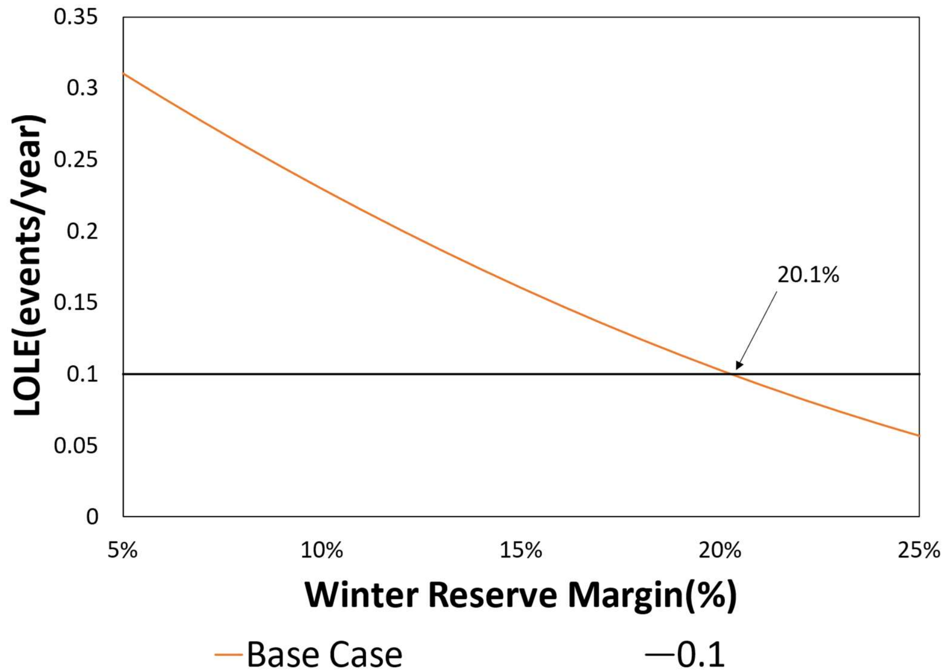


Figure 16. Interconnected LOLE as a Function of PRM

The following figure shows the monthly breakdown of LOLE at the PRM level closest to 0.1 LOLE.

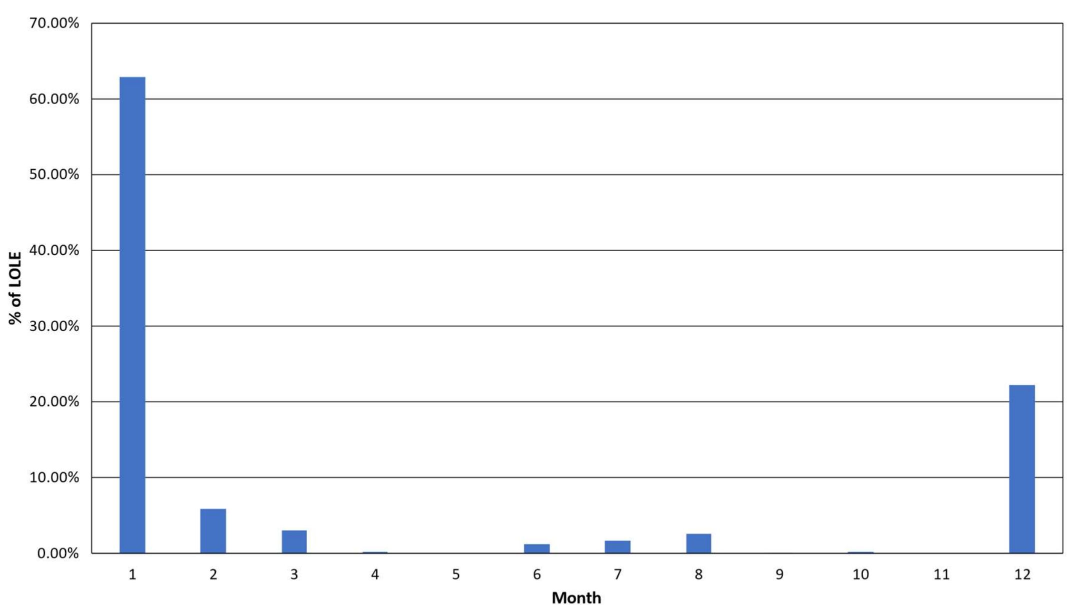


Figure 17. Monthly LOLE at PRM

As the figure demonstrates, the overwhelming majority of the LOLE occurs during the winter months of January, February, and December. The % LOLE by weather year at the PRM closest to 0.1 LOLE is listed in the table below.

Table 11. LOLE by Weather Year at PRM

Weather Year	LOLE	% of LOLE	Weather Year	LOLE	% of LOLE
1980	0.003	3.0%	2001	-	-
1981	0.004	3.7%	2002	-	-
1982	0.015	14.4%	2003	0.0061	5.8%
1983	0.019	18.4%	2004	-	-
1984	-	-	2005	0.0002	0.2%
1985	0.028	26.4%	2006	0.0002	0.2%
1986	0.009	8.2%	2007	0.0013	1.3%
1987	-	-	2008	0.0002	0.2%
1988	-	-	2009	0.0004	0.4%
1989	0.001	0.7%	2010	0.0003	0.3%
1990	-	-	2011	-	-
1991	-	-	2012	0.0003	0.3%
1992	-	-	2013	-	-
1993	-	-	2014	0.0024	2.3%
1994	0.002	2.0%	2015	0.0053	5.1%
1995	-	-	2016	0.0004	0.4%
1996	0.003	3.3%	2018	0.0025	2.4%
1997	-	-	2017	0.0001	0.1%
1998	-	-	2019	0.0002	0.2%
1999	-	-	2020	-	-
2000	-	-	2021	-	-

The following table shows the probability weighted average hourly 12x24 EUE profile (as a percent of the total EUE for the year) for 2026.

Table 12. 2026 Weighted EUE by Hour

	1	2	3	4	5	6	7	8	9	10	11	12
1	0.08%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%
2	0.07%	0.03%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.02%
3	0.17%	0.03%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.07%
4	0.58%	0.07%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.17%
5	2.36%	0.17%	0.21%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.28%
6	5.02%	0.39%	0.48%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.04%
7	17.62%	1.69%	1.29%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	5.95%
8	32.10%	1.36%	1.03%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	11.64%
9	6.08%	0.00%	0.07%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.42%
10	1.85%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.38%
11	0.34%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
12	0.05%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%
13	0.03%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
14	0.02%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
15	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
16	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.05%	0.00%	0.00%	0.00%	0.00%
17	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.05%	0.00%	0.00%	0.00%	0.00%
18	0.01%	0.00%	0.00%	0.00%	0.00%	0.03%	0.03%	0.08%	0.00%	0.04%	0.00%	0.02%
19	0.04%	0.00%	0.00%	0.00%	0.00%	0.17%	0.22%	0.49%	0.02%	0.01%	0.00%	0.14%
20	0.21%	0.00%	0.00%	0.00%	0.00%	0.23%	0.14%	0.21%	0.00%	0.00%	0.00%	0.38%
21	0.30%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%	0.50%
22	0.35%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.30%
23	0.32%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.19%
24	0.08%	0.02%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.12%
Sum	67.69%	3.78%	3.09%	0.01%	0.00%	0.43%	0.40%	0.89%	0.02%	0.05%	0.00%	23.66%

SENSITIVITY RESULTS

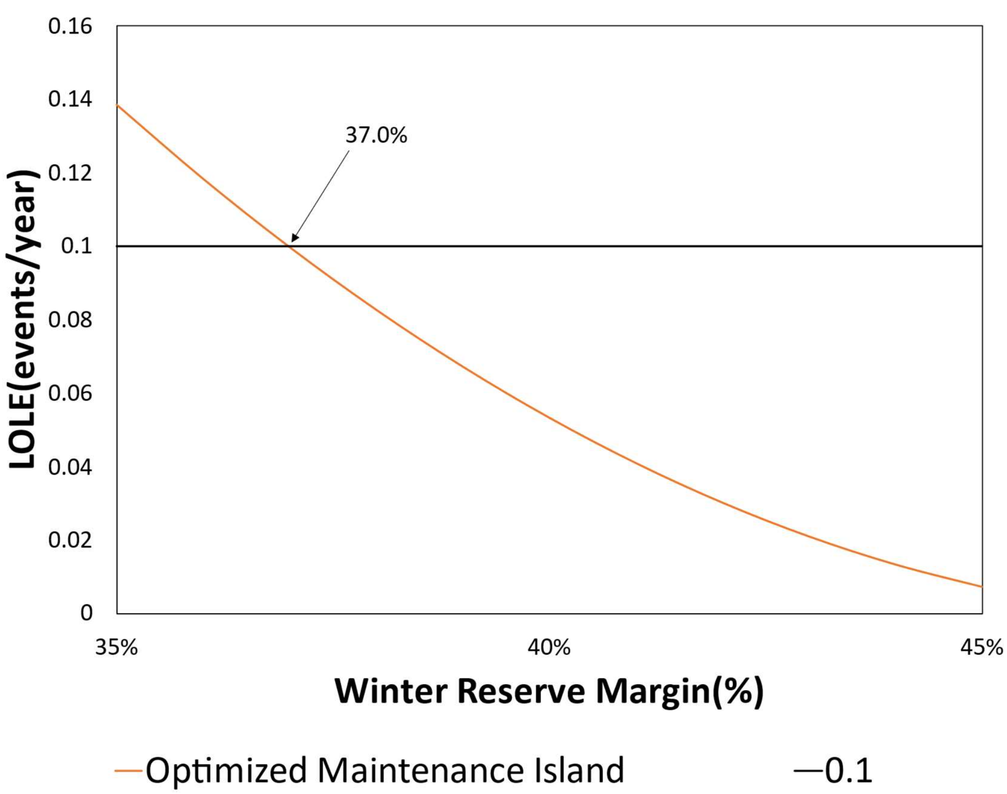
The following sensitivities were performed, with the results from each sensitivity analysis presented in the sub-sections that follow:

- Optimized Islanded Maintenance
- Low Cold Weather Load Response Sensitivity
- High Cold Weather Load Response Sensitivity

OPTIMIZED ISLANDED MAINTENANCE SENSITIVITY

In the optimized islanded maintenance sensitivity, SERVM was given perfect knowledge of each case's load shape in order to optimally plan each unit's scheduled planned maintenance. As Figure 18 shows, if given perfect knowledge of when to plan maintenance, DESC would achieve a 0.1 LOLE reliability with a 37% winter reserve margin.

Figure 18. Optimized Islanded Maintenance



LOW COLD WEATHER LOAD RESPONSE SENSITIVITY

To simulate a low load response sensitivity, loads were re-developed in such a way that loads for DESC were never allowed to exceed the highest load seen in the five year historical data used to train the neural networks. While extreme, this sensitivity and the high load response sensitivity serve as bookends to consider. The low load sensitivity would achieve a 0.1 LOLE reliability at a 16.2% as shown in the following figure.

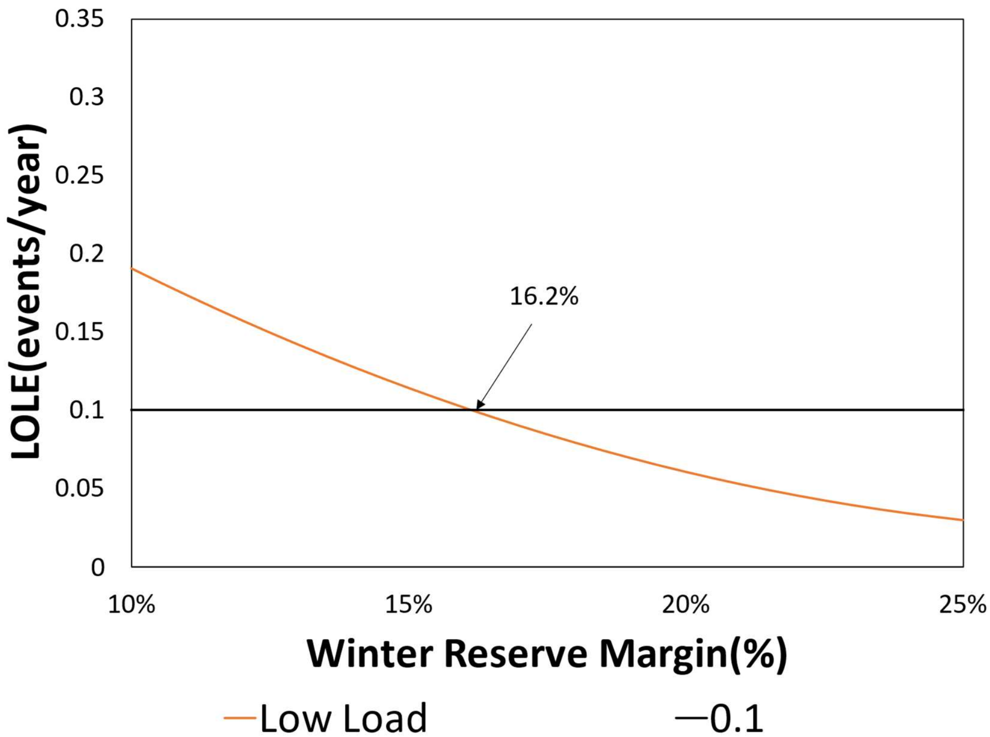


Figure 19. Low Load Response Sensitivity Results

HIGH COLD WEATHER LOAD RESPONSE SENSITIVITY

In February of 2021, ERCOT experienced load variance due to extreme cold weather of approximately +30%[7] versus the normal weather forecast. To simulate a high load response sensitivity, loads were re-developed with an increased load response assumption such that the maximum peak load variance for DESC reached +30%. This sensitivity represents a high bookend for load response. The results of that analysis are shown in the following figure.

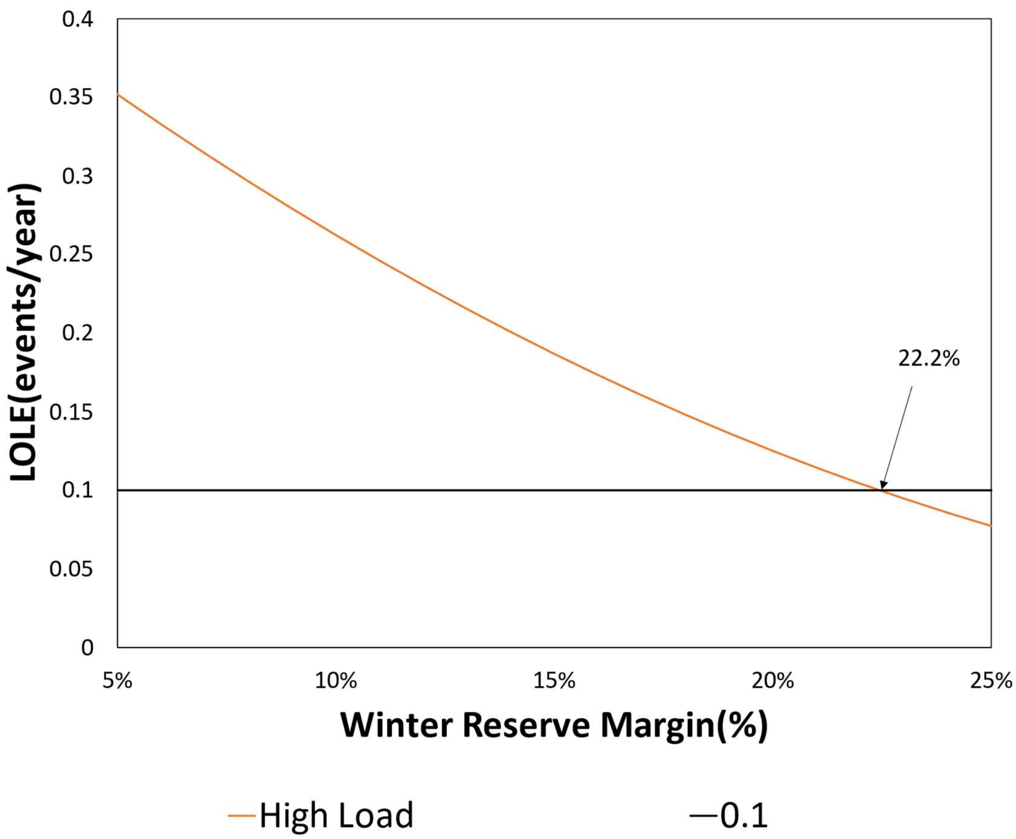


Figure 20. High Load Response Sensitivity Results

[7] Data from ERCOT shows that the winter peaks in February 2021 were approximately 29% above the weather normal forecast. The weather normal forecast going into the winter was 59,567 MW and while actual loads at the coldest temperature were not known precisely due to load shedding procedures, ERCOT projected a peak load of 76,819 MW. This represents a load volatility of 29% (76,819 MW / 59,567 MW)-1) above the weather normal forecast developed prior to the winter season.

ELCC RESULTS

The process used in determining the ELCC of renewables on the DESC system was described in the Determining ELCC subsection of the Study Methodology section of this report above. The results of the Existing and Incremental Portfolio ELCC analyses are as follows in the tables below

Table 13. Existing Portfolio ELCC's

Technology	ELCC(%)
Solar	2.2%
Pumped Storage	98%
Battery	89%

Table 14. Incremental Solar ELCC's

Incremental Solar(MW)	Solar Average ELCC(%)
100	2.70%
600	0.70%
1,100	0.50%
1,600	0.50%

Table 15. Average and Marginal Incremental Storage ELCC's

Incremental Storage(MW)	4 Hour Storage Average ELCC(%)	4 Hour Storage Average ELCC(%)	4 Hour Storage Marginal ELCC(%)	4 Hour Storage Marginal ELCC(%)
	Conservative Operations on Extreme Days	Assumes Economic Arbitrage	Conservative Operations on Extreme Days	Assumes Economic Arbitrage
50	100%	93. %	100%	93%
300	100%	91%	100%	90%
550	99.00%	88%	98%	85%
800	94.80%	86%	88%	80%

The incremental storage ELCC analysis included the assumption that the energy from the storage resources was primarily conserved and dispatched to address reliability issues. This conservative operation of the resources reflects the likely operation if the storage resources were DESC owned/controlled. However, an additional ELCC sensitivity was run where the energy storage resources were dispatched primarily to take advantage of energy arbitrage. As expected, when the storage resources were operated in this manner they showed a lower ELCC. These values would be more appropriate to use if DESC does not have full control of the resource.

CONCLUSIONS

DESC's primary reserve margin requirement should be a winter requirement. Based on the results, a 20.1% winter reserve margin meets the 1 day in 10 year standard and is appropriate for planning purposes. Neighbor assistance plays a vital role in reliability across the year and has been included in this study. While there is uncertainty surrounding extreme cold weather load response, allowing the winter reserve margin to drop below 20% is likely to provide reliability levels lower than DESC's 1 day in 10 year reliability standard.

The summer reserve margin requirement should be considered a secondary requirement. Based on the analysis of the summer LOLE, it can be concluded that a summer reserve margin requirement of 15% equates to an LOLE of 0.015. DESC should continue to observe summer risks but if a 20.1% winter reserve margin is maintained it is expected that this 15% requirement will be automatically met.